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Article

Predict and estimate the current stock prices by using Adaptive Neuro-Fuzzy Inference System

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Abstract: To correctly and accurately predict and estimate the stock prices to get the maximum profit is a challenging task, and it is critically important to all financial institutions under the current fluctuation situation. In this study, we try to use a popular AI method, Adaptive Neuro Fuzzy Inference System (ANFIS), to easily and correctly predict and estimate the current and future possible stock prices. Combining with some appropriate pre-data-processing techniques, the current stock prices could be accurately and quickly estimated via those models. A normalization preprocess for training and testing data was used to improve the prediction accuracy, which is our contribution and a plus to this method. In this research, an ANFIS algorithm is designed and built to help decision-makers working in the financial institutions to easily and conveniently predict the current stock prices. The minimum training and checking RMSE values for the ANFIS model can be 0.103842 and 0.0651076. The calculation of accuracy was carried out using the RMSE calculation. The experiments conducted found that the smallest RMSE calculation result was 0.103842 with training data. Other issuers can use this method because it can predict stock prices quite well.

Keywords: ANFIS algorithm; estimate and predict current stock prices; AI applications in financial implementations; Google stock dataset; prediction accuracy

1. Introduction

As the fast development of AI technologies, such as Fuzzy Inference Systems, machine learning, and deep learning, today various AI-related algorithms have been widely implemented in financial fields to estimate and predict the stock values, currency exchange rates, bonus analyses, and all other related applications [1–7].

Most of the research is concentrated on stock predictions or estimations based on neural networks, machine learning, and deep learning studies. Different and various machine learning algorithms accompanied with some sophisticated additions are applied to stock analyses and predictions to improve the accuracy of predictions on stock markets. Chong et al. [8] reported using an Ensemble of Deep Neural Networks to predict performance for stock markets. Yu [9] developed an algorithm based on deep learning and neural networks to improve the analyses for economic and financial data. Polepally et al. [10] and Pardeshi and Kale [11] reported using machine learning and deep learning algorithms to improve the prediction accuracy for current stock prices. Singh et al. [12] and Lin et al. [13] developed a novel multivariate recurrent neural network and a new convolutional neural network with a long short-term memory combined model to estimate the current stock prices and their tendency.

Singh et al. [14] performed comparative studies and analyses for different stock price prediction techniques developed in recent years. Roy and Tanveer [15] developed an algorithm to forecast stock price by using the DeepNet method. Instead of using any traditional machine learning model, Tarsi et al. [16] utilized a Long Short Term Memory (LSTM), which is a variation of a machine learning model, to predict the stock price. Mandee et al. [17] utilized an explainable artificial intelligence XAI to predict stock market trends.

Chinprasatsak et al. [18] reported using a neural network for forecasting high and low prices in the foreign exchange market. Alamsyah and Aprillia [19] and Aggarwal and Sahani [20] performed some studies in comparisons of the foreign currency prediction performance with neural network algorithms. Bui et al. [21] and Singh et al. [22] reported using neural networks and CNN-RNN-based hybrid machine learning models to predict the currency exchange rate. Sarmas et al. [23] performed a comparison study among different machine learning classification methods used for currency exchange rate trends. Tak and Logeswaran [24] also developed a foreign currency prediction method based on machine learning techniques.

To correctly and accurately predict and estimate the current stock prices to get the maximum profit via different AI methods, some correct AI models are necessary with popular algorithms, such as Adaptive Neuro Fuzzy Inference System (ANFIS). Combining with some appropriate pre-data-processing techniques, the current stock prices could be accurately and quickly estimated via those models. In this research, an ANFIS model is designed and built to help decision-makers working in the financial institutions to easily and conveniently predict the current stock prices.

Stock prices are changed at any moment, and they may vary significantly day by day, month by month, and year by year. Due to the heavy complexity and unforeseen variations in the current market, to correctly and accurately predict the stock prices, the following factors and operational steps need to be taken:

1) The changing or variation of the stock prices can be considered a periodic function, and this period could be 3 months, 6 months, or longer, which depends on the target period for each research. In our case, we used 3 months as a period.
2) Based on the assumption above, we utilized the Google Stock dataset to train and check our target ANFIS model.

This study is divided into 5 Sections; after this introduction, an introduction to two Google Stock datasets used as the training and checking for AI models is provided in Section 2. The ANFIS and its implementations are discussed in Section 3. The experiment studies and results are given in Section 4. The conclusion and future works are provided in Section 5.

2. Introduction to Google stock dataset

Two Google Stock datasets [25], one containing 5-year stock transaction records from 3 January 2012 to 30 December 2016 and the other including 1-month stock transaction records from 3 January 2017 to 31 January 2017, are utilized in this study. The first one is used as the training and checking data for ANFIS and DL models, and the second works as the testing and validation purpose for those models.

Each dataset contained six columns: Date, Open, High, Low, Volume, and Close, with both 5-year and 1-month stock price records. Each related column can be mapped to the Opening price, Highest price, Lowest price, transaction Volume, and Closing price. For our study, we only need four of them: Open, High, Low, and Close. In fact, we use the first three columns, Open, High, and Low, as inputs and the Close column as the output, as shown in **Figure 1** for our ANFIS structure.

A critical key issue in using that data to train, check, and test our ANFIS or DL models is the data pre-processing. As everybody knows, the stock prices are changed or varied in every moment, not each day, and the amounts they changed are significant with a relatively wider range, or even dynamically, for a period of time. This provided a challenging issue when using ANFIS, especially using the fuzzy rules, to estimate the output or the closing price due to the significant variations in the price values. In the worst case, the ANFIS could not perform its FIS function due to the out-of-bounds input values with too big different price values for different time periods.

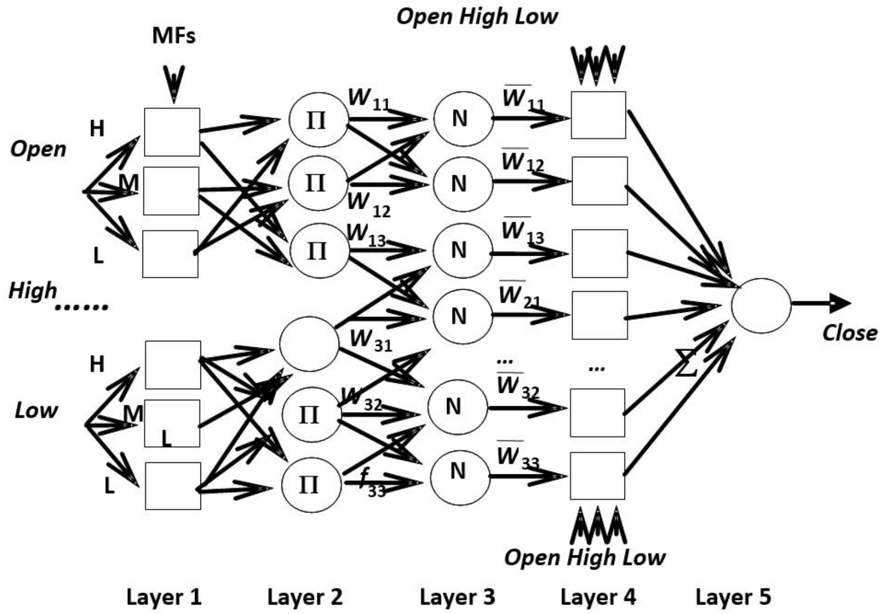

Figure 1. A typical structure of ANFIS.

To effectively solve this key issue, we need to preprocess that data, exactly to perform a normalization job for that data to enable them to be used in our model training and checking. In summary, we only take care of those relative changing values on the prices, but not for the absolute changing values, and this is good enough for us since we only pay our attention to the changing values in trends or tendency.

3. Adaptive Neuro-Fuzzy Inference System

The so-called ANFIS is exactly a combination of two soft-computing techniques: Artificial Neural Network (ANN) and Fuzzy Inference System (FIS), which was first introduced by Jyh-Shing Roger Jang in 1992 [26]. The FIS used a Sugeno Fuzzy Inference System, and its structure is similar to a multilayer feedforward neural network structure, but the difference is that the links between nodes in ANFIS define the signals' flow direction, and there are no associated weight factors with the links. It consists of a network of neurons that communicate between the input and hidden layers, as well as the hidden and output layers.

Figure 2 shows an illustration of the ANFIS working process with two inputs, *x* and *y* [27]. After the input layer, the second layer is to fuzzificate the inputs to fuzzy variables with the mbership function format. The third and the fourth layers are used to perform the fuzzy inference process to derive the weighted fuzzy outputs. The final or the fifth layer is used to perform the defuzzification process to obtain the real outputs.

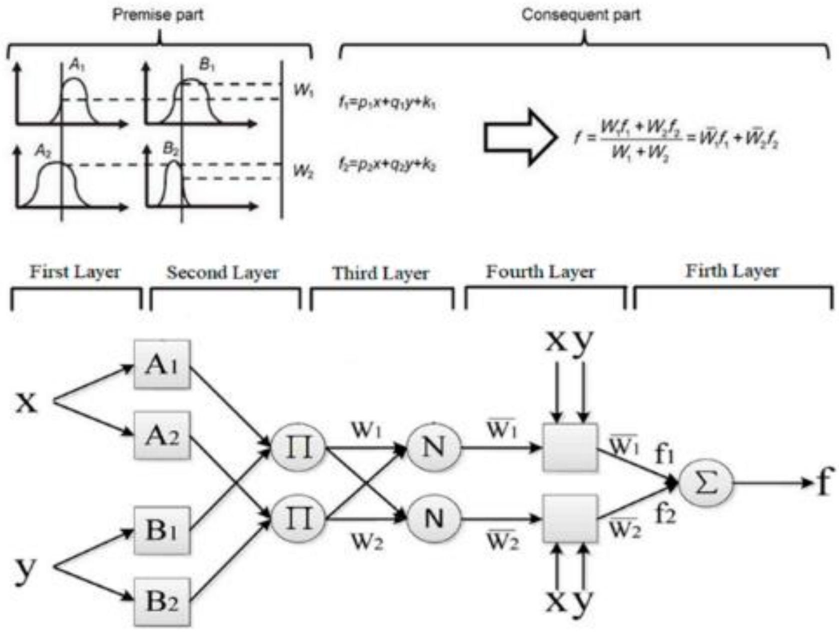

Figure 2. An illustration of ANFIS working process.

Each layer consists of neurons constructed according to the principles of fuzzy control. **Figure 1** shows a Sugeno fuzzy model with 27 rules along with a corresponding ANFIS architecture. In our case, a total of 27 rules in the method of "If-Then" for the Sugeno model are considered with *x* and *y* as inputs and *f* as output [28]. 27 rules are defined as below (three input columns–*Open*, *High*, *Low*; L: value low, M: value mid, H: value high):

R_1: If *Open* is L and *High* is L, and *Low* is L,

then $f_{111} = p_{111}Open + q_{111}High + r_{111}Low + c_{111}$

R_2: If *Open* is L and *High* is L, and *Low* is M,

then $f_{112} = p_{112}Open + q_{112}High + r_{112}Low + c_{112}$

R_3: If *Open* is L and *High* is M, and *Low* is L,

then $f_{21} = p_{113}Open + q_{113}High + r_{113}Low + c_{113}$

R_4: If *Open* is L and *High* is M, and *Low* is M,

then $f_{22} = p_{211}Open + q_{211}High + r_{211}Low + c_{211}$

…

The membership functions (MFs) for three inputs, Open, High and Low are shown in **Figure 3**. Each of three input variables has three MFs, **in1mf*i*** (i = 1 ~ 3) with Gaussian waveforms (**gaussmf**) as the MF distributions. In **Figure 2**, only the MFs for input1 (Open) are displayed as an example with an input range of $279 ~ $786. The distributions of these MFS are based on estimations of the values in the

Google Stock Price datasets, **Google_Stock_Price_Train.csv** and **Google_Stock_Price_Test.csv**, respectively.

Figure 4 shows the envelope or surface of this ANFIS model with input1 and input2 as input variables. The vertical direction or *z*-axis represents the stock closing prices that are a function of both input variables. **Figure 5** displays the structure for this ANFIS model.

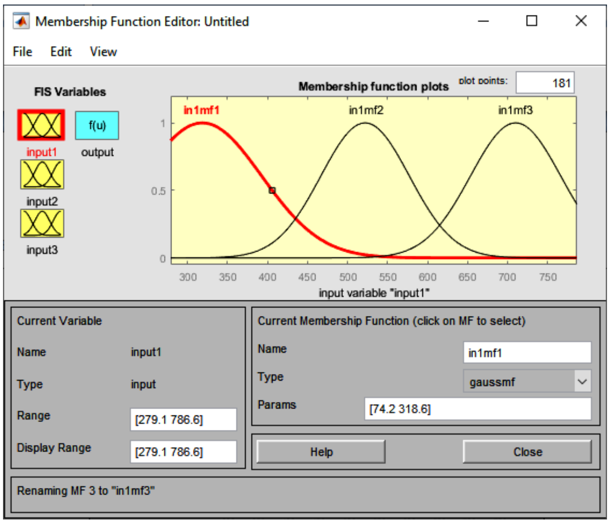

Figure 3. The membership functions of the input variable—Open.

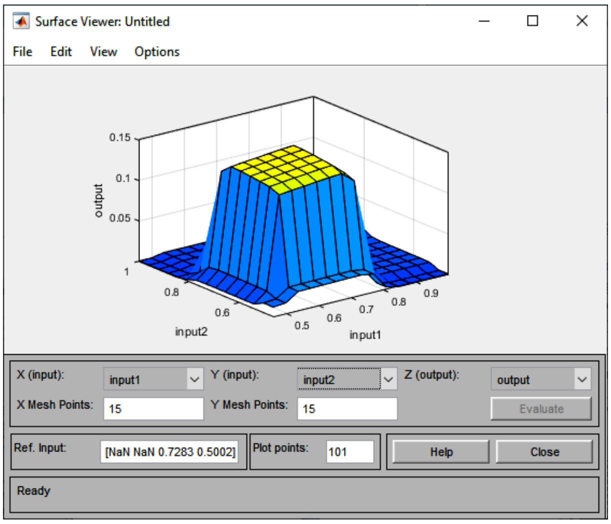

Figure 4. The envelope or the surface of the ANFIS.

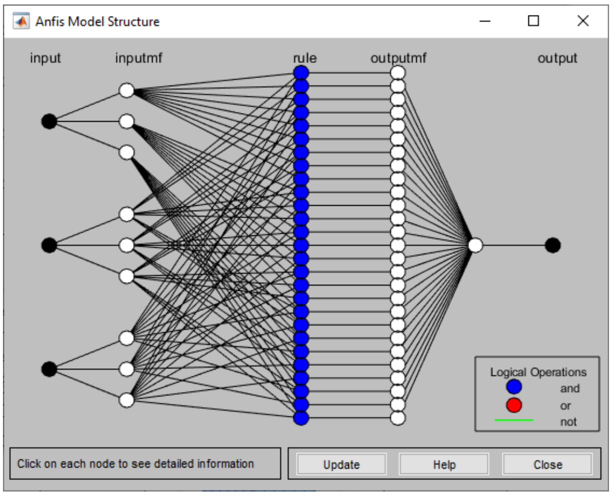

Figure 5. The structure of this ANFIS model.

4. The experimental results

By using the Google Stock 5-year dataset as the training and checking data to train and check our ANFIS model, the training and testing results are shown in **Figures 6** and **7**. The prediction or estimation for current stock prices based on training and checking the model is shown in **Figure 8**.

The RMSE values for both training and testing are shown below:

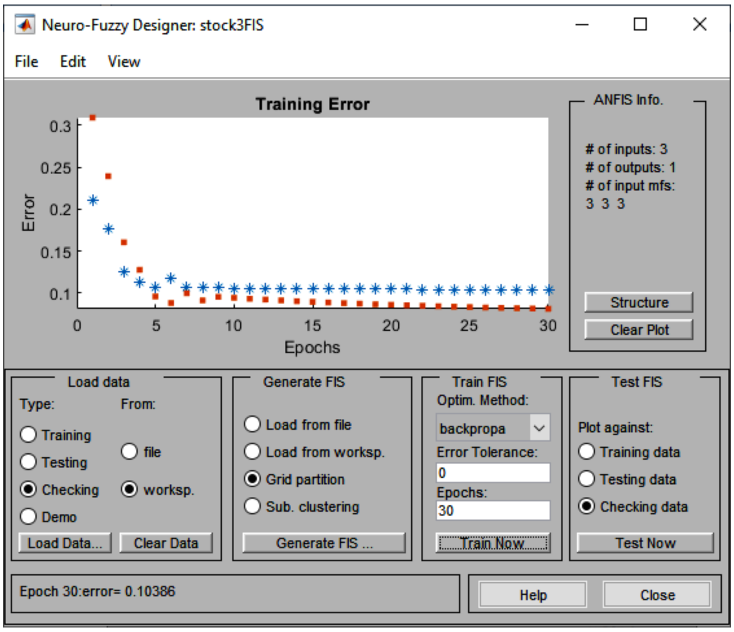

Figure 6. The training result for ANFIS model.

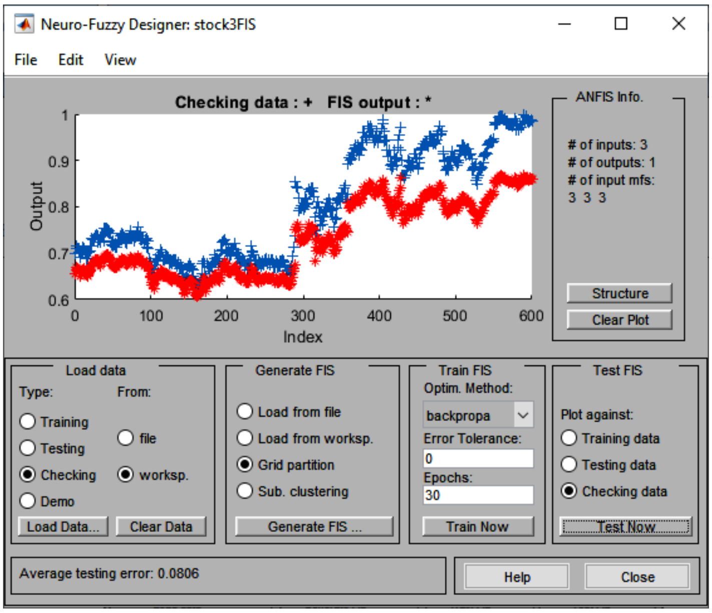

Figure 7. The testing result for the ANFIS model.

Designated epoch number reached. ANFIS training completed at epoch 2.

Minimal training RMSE = 0.103842

Minimal checking RMSE = 0.0651076

The Root Mean Squared Error (RMSE) is one of the major performance indicators for a regression model. It measures the average difference between stock values predicted by our ANFIS model and the actual stock values. It provides an estimation of how well the model is able to predict the target stock value (accuracy).

It can be found from **Figure 7** that the predicted and the actual stock price values are very close in tendency or trend, which is our objective since we do not take care of any single stock price value, but instead we only take care of the tendency or trend of stock price variations in a certain time window. That is our target or objective, and it enables us to find the peak or valley stock prices to help us to make decisions to invest or sell out our stocks in time to get the maximum benefits.

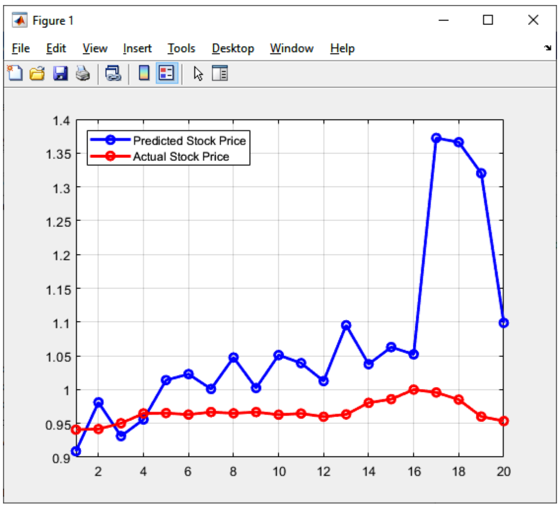

Figure 8. A comparison between the predicted and actual stock prices.

To confirm the general prediction effectiveness of using our method, we tested it with another popular stock dataset, the NASDAQ Stock Market Dataset [29]. The RMSE values for that prediction process are;

Minimal training RMSE = 0.00837042

Minimal checking RMSE = 0.123309

Figure 9 shows the comparison between the predicted and actual stock prices for NASDAQ stock dataset. It can be found that the tendency of both the predicted and the actual stock prices is very close.

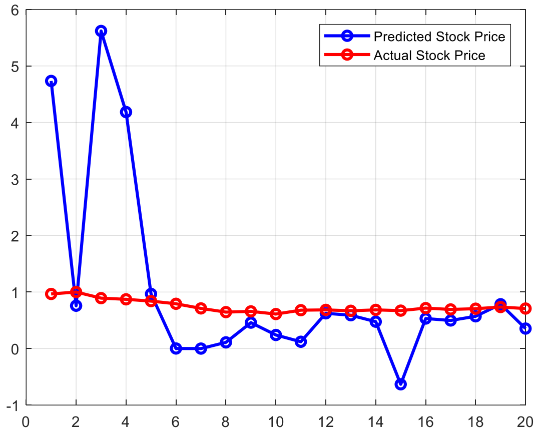

Figure 9. A comparison of predicted and actual stock prices for NASDAQ stock dataset.

5. Conclusion

With the help of MATLAB Fuzzy Logic and Deep Learning Toolboxes as well as Google Stock dataset, we develop an AI model, exactly an ANFIS model, to perform prediction and estimation for stock prices. First, we utilized Google Stock 5-year dataset to train and test our ANFIS model. To confirm and check the effectiveness and accuracy, we utilized another Google Stock 1-month dataset to validate the trained model. The evaluation result shows that the prediction accuracy is good enough for us to estimate the current stock prices, and the prediction results are acceptable.

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